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The Effect of Point Density on Point Cloud Filtering Performance
Nokta Bulutu Yoğunluğunun Filtreleme Performansı Üzerine Etkisi

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Abstract

Point cloud filtering is an important step in Digital Terrain Model (DTM) production. Despite the fact that a great body of research has been conducted in this area so far, there are still some problems that have not yet been solved, especially in complex terrains. The fact that the use of user-defined parameters within the presented point cloud filtering methods, and the difficulty of parameter estimation in parallel to the increase in the topography slope and above-ground object diversity, decreases the filtering success. Another problem is the proper specification of the point cloud density to be studied. Point cloud density, which is generally specified considering the ground sampling distance of the DTM, influences the success of the point cloud filtering process, therefore, the accuracy of the DTM produced. In this study, five Unmanned Aerial System (UAS)-based point clouds of different densities were filtered using two different point cloud filtering algorithms Cloth Simulation Filtering (CSF) and gLiDAR to examine the impacts of the point cloud density on filtering success. It was found that the point cloud filtering performance decreased as the point density increased.

Keywords: *Point cloud filtering, Digital Terrain Model, CSF, gLiDAR*

Özet

Nokta bulutu filtreleme sayısal arazi modeli üretiminde çok önemli bir aşamadır. Şimdiye kadar bu alanda pek çok çalışma yapılmıştır ancak, özellikle kompleks zeminlerde hala aşılamayan bazı sorunlar vardır. Sunulan yöntemlerde çoğunlukla kullanıcı girişli parametreler kullanılması ve parametre kestiriminin, topografya eğimi ve zemin üstü obje çeşitliliği arttıkça zorlaşması filtreleme başarısını düşürmektedir. Bir diğer sorun ise çalışılacak nokta bulutu yoğunluğunun uygun şekilde belirlenmesidir. Üretilecek sayısal arazi modelinin yer örnekleme aralığına göre belirlenen yoğunluk aynı zamanda nokta bulutunun filtreleme başarısını ve dolayısıyla elde edilecek sayısal arazi modelinin hassasiyetini de etkilemektedir. Bu çalışmada, 5 farklı yoğunlukta üretilen insansız hava aracı tabanlı nokta bulutları, nokta bulutu yoğunluğunun filtreleme başarısına etkilerini incelemek için Cloth Simulation Filtering (CSF) ve gLiDAR filtreleme algoritmaları kullanılarak filtrelenmiştir. Elde edilen sonuçlara göre nokta bulutu yoğunluğu arttıkça filtreleme başarısının düştüğü görülmüştür.

Anahtar kelimeler: *Nokta bulutu filtreleme, Sayısal Arazi Modeli, CSF, gLiDAR*

1. Introduction

The advent of sophisticated Unmanned Aerial Systems (UASs) in the last years has opened an era of monitoring the surface of the Earth. The camera systems mounted on the UASs are used not only for surveillance purposes, but also for extracting meaningful information from the features on the ground. In recent years, 3D modelling of the surface of the Earth has been one of the most common uses of data obtained from such camera systems. The UAS data provide comprehensive and accurate information for land cover features. As a matter of fact, the accuracy of the data obtained from UASs has increased so much that it has become competitive with the accuracy obtained from terrestrial measurements.

3D reconstruction of the land objects relies on aerial photogrammetry, whose primary objective is to produce point clouds of the land objects through the use of aerial photos acquired from the cameras mounted on the UASs. The produced point clouds are used to derive further products, including Digital Surface Models (DSMs), Digital Terrain Models (DTMs) and orthophotos. A DTM, which models the elevation information of the bare Earth surface, is an important source of data in many remote sensing applications. In recent years, DTMs have been used for various purposes, including change detection (Ali-sisto and Packalen, 2017), tree detection (Demir, 2018), flood damage assessment (Arrighi and Campo, 2019), estimating forest stand parameters (Yilmaz and Güngör, 2019), determination of waterlogged soil areas (Boiarskii et al. 2019), landslide susceptibility mapping (Karakas et al. 2020), detection of flood zones (Douass and Ait Kbir, 2020) etc.

To produce a DTM, point clouds are first filtered to extract the topography of the bare Earth surface. Point cloud filtering is the removal of the points of the above-ground features such as trees, buildings, bridges etc. In general, point cloud filtering is a challenging process and its success is dependent on many factors including;

- The topography of the application area (Serifoglu Yilmaz et al. 2018). Point cloud filtering is a lot easier on topographies with slight slopes. On the other hand, point cloud filtering performance is expected to decrease on complex topographies.
- The mathematical background of the point cloud filtering method used. The literature has reported a large number of point cloud filtering methods so far and each one of them performs with a different mathematical approach.
- The size and shape of the above-ground features (Serifoglu Yilmaz et al. 2018). The point cloud filtering process becomes more challenging on topographies with varying-sized and -shaped above-ground features.
- The proximity of the above-ground objects. If the application area contains many above-ground features that are very close to or interlocking with each other, point cloud filtering performance is expected to decrease.
- The experience of the analyst. An experienced analyst is aware of which point cloud filtering method may be more successful, considering the topography of the application area. On the other hand, inexperienced analysts tend to choose inefficient filtering algorithms and filtering parameters, committing greater filtering errors.

Another important factor affecting the performance of the point cloud filtering process is the density of the point cloud to be filtered. This factor plays a vital role in point cloud filtering performance, impacting the accuracy of the produced DTM. Hence, this study aims to examine the impacts of the point cloud density on point cloud filtering success. To do so, five UAS photogrammetry-based point clouds with different densities were filtered with two commonly-used point cloud filtering methods Cloth Simulation Filtering (CSF) (Zhang et al. 2016) and gLiDAR (Mongus and Žalik, 2012) and the filtering results were evaluated in this manner.

The reminder of the paper is as follows: Section 2 will provide information for the point cloud generation process and point cloud filtering methods used. Section 2 will also give information on the metrics used to evaluate the point cloud filtering results. Section 3 will evaluate the point cloud filtering results using the quality metrics. Finally, Section 4 will present the concluding remarks.

2. Application

2.1 Point Cloud Generation

This study was conducted in the Karadeniz Technical University campus in Trabzon, Turkey. The study area includes different-sized buildings and trees. The study area is shown in Figure 1.

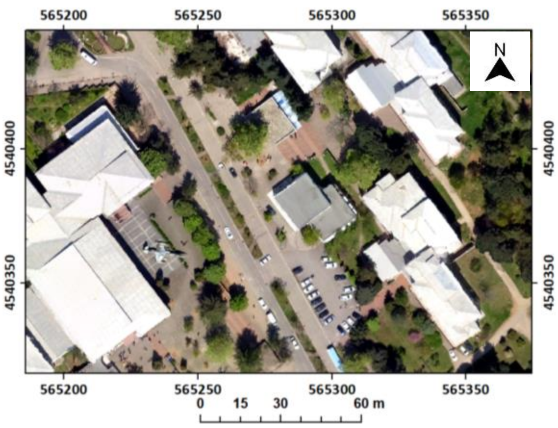

Figure 1. Study area

The point clouds used in this study were produced with 256 aerial photos acquired from an altitude of 185 m. The aerial photos were taken by a RICOH GR DIGITAL IV camera, which is mounted on a Gatewing X100 UAS. The aerial photos were processed in the Agisoft Photoscan Professional (APP) software to generate the initial point cloud having a point density of 0.5 point/m^2. Then, denser point clouds were produced in the APP software. The software uses the depth information for each image capture point to densify the point clouds (Agisoft Photoscan Professional software user manual, 2016). Point densification process resulted in point clouds with densities of 1.6 point/m^2, 5.4 point/m^2, 19.6 point/m^2, 74.5 point/m^2 and 272.2 point/m^2, which will herein be referred as D1, D2, D3, D4 and D5, respectively.

2.2 Point Cloud Filtering

This study used the CSF and gLiDAR algorithms to filter the produced point clouds. This sub-section will provide details on how these algorithms were performed.

2.2.1 CSF

The CSF method is based on the principle of dropping a piece of cloth onto an inverted land surface (Zhang et al. 2016). In such a case, the shape of the cloth forms the DTM of the application area. The very first step of the CSF method is to invert the point cloud. Then, a user-defined grid resolution parameter comes into play to define the number of cloth particles to be dropped. The points and particles are transformed into a horizontal plane and a corresponding point is specified for all cloth particles. The terrain point that intersects with the cloth particle is found and its height is specified as the ‘intersection height value’. If the intersection height value is greater than the current height value, then the particle is moved back to the position of the intersection height value and labelled as unmovable (Zhang et al. 2016). In each iteration, the distances between the point cloud and particles are determined. Each point whose distance to the particles is greater than a user-defined threshold (i.e. class threshold parameter) is labelled as a non-ground point (Zhang et al. 2016; Serifoglu Yilmaz et al. 2018). The cloth particles move down and up due to the internal and external (i.e. gravity) forces until the desired height variation or a maximum iteration number is achieved (Zhang et al. 2016). Apart from the aforementioned parameters, the CSF method employs two more parameters, the time step and rigidness. The former is responsible for controlling the movements of the particles, whereas the latter is used to define the terrain type (Zhang et al. 2016; Serifoglu Yilmaz et al. 2018. The optimum values of the parameters used within the CSF algorithm were found by trial-and-error. The parameter values used for the CSF algorithm are shown in Table 1.

Table 1. Parameter values used for the CSF algorithm

Parameter	Point cloud				
	D1	D2	D3	D4	D5
Rigidness	1	1	2	2	2
Grid resolution	2	2	1	1	2
Class threshold	1	1	1	1	1
Time step	1	1	0.6	0.6	1
Maximum iteration number	500	500	500	500	500

2.2.2 gLiDAR

The gLiDAR technique removes the non-ground points considering the height differences between the above-ground objects and their surroundings (Mongus and Žalik, 2012). This technique generates a surface towards the ground using the thin plate spline interpolation whilst filtering off the points belong to the above-ground objects by employing a window whose size decreases gradually. The height differences between the points and interpolated surface are used to filter off the non-ground points. A top-hat transformation is employed to compare the height differences between data points. The obtained non-ground points are substituted by the interpolated points to be used in the next iteration, where a smaller-sized window is used for filtering. The gLiDAR algorithm iterates until the required DTM resolution is achieved (Mongus and Žalik, 2012; Serifoglu Yilmaz et al. 2018). The gLiDAR technique uses a maximum size parameter value to filter off the largest object in the application area. Apart from this, the parameters n and b are employed to decide whether or not a candidate point is considered a non-ground point, and to specify the ratio between the sizes of the land objects and their responses in the top-hat space, respectively (Korzeniowska et al. 2014; Serifoglu Yilmaz et al. 2018). The optimum values of the parameters used within the gLiDAR algorithm were found by trial-and-error. Table 2 presents the parameter values used for the CSF algorithm.

Table 2. Parameter values used for the gLiDAR algorithm

Parameter	Point cloud				
	D1	D2	D3	D4	D5
n	0	0	0	0.01	0
b	0.4	0.8	0.5	0.02	0.5
Maximum size	50	50	55	45	50

2.3 Evaluation of the Point Cloud Filtering Results

In the literature, point cloud filtering results are generally evaluated with three quality metrics as Type I Error (TIE), Type II Error (TIIE) and Total Error (TE) (Sithole and Vosselman, 2004; Montealegre et al. 2015; Serifoglu Yilmaz and Gungor, 2018). These errors are computed through omission and commission errors. The omission error is defined by the number of ground points classified as non-ground, whereas the commission error is defined by the number of non-ground points classified as ground. The TIE, TIIE and TE are computed as (Sithole and Vosselman, 2004; Serifoglu et al. 2016);

$$TIE = \frac{OE}{GP} \tag{1}$$

$$TIIE = \frac{CE}{NGP} \tag{2}$$

$$TE = \frac{OE + CE}{GP + NGP} \tag{3}$$

where, CE, OE, GP and NGP stand for the commission error, omission error, number of reference ground points and number of reference non-ground points, correspondingly. Since it is not practical to examine the performance of the filtering result using all points of the study area, the method suggested by Zhang et al. (2003) and Zhang and Whitman (2005) was used for accuracy assessment. This method suggests to use randomly selected points for accuracy assessment. At this point, the question as to how many reference points should be used arises. The minimum number of required random points (n_{min}) was obtained with the Multinominal Approach suggested by Congalton and Green (1999). The mathematical definition of this approach is given as;

$$n_{min} = \frac{b}{4a_d^2} \tag{4}$$

where, $b = ci/n_c$. n_c, ci, and a_d define the number of classes, confidence interval and desired accuracy, respectively. This study considered a ci of 95%, which led to an a_d of 0.05. The study area can be categorized into two classes as ground and non-ground, which resulted in a b of 0.025. According to the χ^2 distribution table, 0.025 corresponds to 5.02 in one degree of freedom. Finally n_{min} was computed as 502. In light of this, accuracy assessment was done with 8000 reference points (4000 points for each class), which were randomly selected from the D1 point cloud. The same reference points were also used for the other point clouds for comparison.

3. Results and Discussion

Table 3 presents the quality metric values determined from the filtered point clouds. The best metric values are shown bold in the table. As seen in the table, both the CSF and gLiDAR methods were found to misclassify the ground points as the point density increased. The TIEs computed from the CSF and gLiDAR results range between 10.65% - 35.53% and 6.05% - 75.78%, respectively. On the other hand, both filtering methods were found to be more successful in removing the non-ground points as the point density increased. Table 3 also shows that the TIIEs obtained from the CSF and gLiDAR results vary between 3.20% - 17.10% and 3.15% - 19.73% correspondingly. It can also be seen in Table 3 that the performance of both filtering methods decreased as the point density increased. The TEs calculated from the CSF and gLiDAR results range between 13.88% - 19.74% and 10.98% - 39.46%, respectively.

Table 3. Quality metric values computed from the filtered point clouds

Point cloud	CSF			gLiDAR		
	TIE	TIIE	TE	TIE	TIIE	TE
D1	**10.65%**	17.10%	**13.88%**	**6.05%**	15.90%	**10.98%**
D2	26.15%	7.80%	16.98%	26.20%	19.73%	22.96%
D3	32.80%	3.73%	18.26%	52.80%	4.20%	28.50%
D4	34.65%	**3.20%**	18.93%	71.00%	3.25%	37.13%
D5	35.53%	3.95%	19.74%	75.78%	**3.15%**	39.46%

As depicted in Table 3, the best TIEs of 10.65% and 6.05% were achieved from the CSF and gLiDAR results of the D1 point cloud, respectively. On the other hand, the optimum TIIEs of 3.20% and 3.15% were obtained by the point clouds produced through the filtering of the D3 and D4 point clouds using the CSF and gLiDAR algorithms, correspondingly. As seen in the table, the CSF and gLiDAR results of the D1 point cloud led to the optimum TEs of 13.88% and 10.98%, respectively.

The most important factor in point cloud filtering is to achieve the best balance between TIE and TIIE. This may not always be possible on complex terrains. The fact that the performances of the employed filtering algorithms are pretty much dependent on user-defined parameters increases filtering errors. Because users usually focus much on removing non-ground points especially on complex terrains. However, in such terrains, proper removal of non-ground points is likely to remove a certain amount of ground points either. This becomes more evident as the point density increases. As seen in Table 3, the TIEs dramatically increased as the point density increased. On the other hand, interpolating new points to densify the D1 point cloud produced too many points near the above-ground objects, which made it very challenging to specify the best parameter values to filter off the non-ground points, leading to the removal of points more than necessary.

Filtering a point cloud with a relatively lower point density enables the filtering result to be examined more successfully and easily. The misclassification errors on ground points can be easily noticed. This is, of course, not so easy in cases where point clouds of higher densities are used. On the other hand, working with lower-density point clouds is time-efficient and requires less system sources. However, point density is very important for the DTM to be generating. Producing a high spatial resolution DTM from a lower-density point cloud is likely to lead to greater interpolation errors on the third dimension.

4. Conclusion

This study investigates the impacts of the point density on point cloud filtering performance. To do so, five UAS-based point clouds of different densities were filtered with two state-of-the-art filtering algorithms CSF and gLiDAR. The experiments revealed that the optimum filtering performance was achieved with lower-density point clouds and the filtering success decreased as the point density increased. The filtering performances of the used algorithms were also found to be highly dependent on the parameter values defined by the user. Both filtering algorithms failed to find a good balance between the omission and commission errors committed, which was mainly due to the fact that the study area included many large and complex-shaped above ground features, making the filtering more challenging.

The point density, filtering performance, interpolation technique used and desired spatial resolution are the most important factors that affect the quality of the DTM produced. Further studies will focus on the investigation of the effects of point density on the elevation accuracy of the DTM to be produced.

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